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The Contributions of Search and Human Capital to Earnings Growth Over the Life Cycle

by

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The Contributions of Search and Human Capital to Earnings Growth Over the Life Cycle

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Abstract

This paper presents and estimates a unified model where both human capital investment and job search are endogenized. This unification enables us to quantify the relative contributions of each mechanism to life cycle earnings growth, while investigating potential interactions between human capital investment and job search. Within the unified framework, the expectation of rising rental rates of human capital through job search gives workers more incentive to invest in human capital. In addition, unemployed workers reduce their reservation rental rates and increase their search effort to leave unemployment quickly to take advantage of human capital accumulation on the job. The results show both forces are important for earnings growth and the interactions are substantial: human capital accumulation accounts for 31% of total earnings growth, job search accounts for 46%, and the remaining 23% is due to the interactions of the two.

Keywords: Human Capital, Job Search, Life Cycle, Earnings Growth.
JEL codes: J24, J64, D91.

1 Introduction

A well established fact in labor economics is that the life cycle earnings profile is increasing and concave. In their recent review, Rubinstein and Weiss (2006) discuss three leading sources for this pattern of earnings growth: human capital accumulation, job search and learning about job, worker or match quality. Human capital theory argues that workers invest in human capital when they are young thus forgoing earnings and reaping the returns to investment when they become old. Search theory argues that workers climb up a job ladder, moving from low-paying to high-paying jobs. When they are young, workers are more likely to be in the lower tail of the earnings distribution. This triggers job-to-job mobility associated with higher growth. As they age, the chance of accepting better outside options declines and fewer job-to-job transitions and lower growth results. With learning earnings on the job change as information is revealed and workers move from poor matches to better ones resulting in across job earnings growth as well. Once the information has been revealed and a good match attained growth subsides. All three of these explanations have been studied extensively on their own and in isolation each can reproduce the observed shape of the life cycle earnings profile if not the full amount of growth.

Recently a new literature on quantifying the relative contributions of these sources of life cycle earnings growth has developed. For the most part this new literature has focussed on modeling the combination of human capital accumulation and job search.[1] Understanding the relative contributions of human capital accumulation and job search to life cycle earnings growth is important since they have different policy implications concerning training on the one hand and labor market mobility on the other hand. With very few exceptions this new literature uses structural models that treat the human capital accumulation process as deterministic through an exogenous learning-by-doing framework. Furthermore, they also commonly treat the search process as exogenous (constant job offer arrival rates). There are two papers that treat the search process as exogenous but endogenize the human capital accumulation process. In a largely conceptual rather than quantitative analysis, Rubinstein and Weiss (2006) endogenizes human capital using a Ben-Porath style investment function. Michelacci and Pijoan-Mas (2011) endogenizes the hours decision within a learning-by-doing human capital accumulation model with exogenous search. However, their focus is on inequality and not life cycle earnings growth. A common result in this literature is that human capital is found to explain more earnings growth over the life cycle than search. A recent exception is Bagger et al. (2011) who find that, even with human capital playing a dominant role early in the life cycle, search quickly overtakes human capital and dominates earnings growth by the end of the life cycle.

[1] Examples include Bunzel et al. (1999), Bagger et al. (2011), Barlevy (2008), Omer (2004), Yamaguchi (2010), Burdett et al. (2011), Sim (2009), Carrillo-Tudela (2010), Prat (2010) and Pavan (2011). Schönberg (2007) and Dustmann and Meghir (2005) are two examples using reduced form analysis. Sanders (2011) is a recent paper that combines learning with job search.

In contrast to these assumptions, we present a unified model where both human capital investment and search intensity are endogenized to quantitatively examine the relative contributions of both mechanisms and their potential interactions to earnings growth over the life cycle. The decision-making in terms of human capital investment and job search are likely to be different within a unified framework. Consider a unified model where workers, facing a distribution of the rental rate of human capital, decide how much time to invest in general human capital within a Ben-Porath style investment model and how much effort to spend searching for a better job. Under this scenario, there are likely three interactions between human capital accumulation and job search. First, workers will likely invest more in human capital than they would without job search and with only a fixed rental rate of human capital. This is due to the upward drift in the distribution of the rental rate of human capital, inherent in the search model. Second, workers will likely spend more effort searching with human capital accumulation than without. This is because, without human capital accumulation, the return to search is only realized for a fixed level of human capital. With human capital accumulation, the return to search is greater since it is now realized for growing human capital. Third, because of human capital accumulation on the job, workers will likely reduce their reservation rate while unemployed in order to get a job to start accumulating human capital.[2] For the most part the existing literature has been able to identify only a subset of these interactions. For example, Omer (2004) and Yamaguchi (2010) find that the reservation wage (or match quality) is lower with exogenous human capital accumulation than without, while Rubinstein and Weiss (2006) point out that workers will invest more in human capital with exogenous job search than without.

In addition to quantifying the full extent of the interactions between human capital investment and job search effort over the life cycle, we examine whether allowing for the interactions within a unified model changes the implications for earnings growth. Since Rubinstein and Weiss (2006) established that the amount of human capital accumulated with (exogenous) job search and without is different, it follows from the arguments above that the amount of human capital accumulated will be different if the job search process is then endogenized. Furthermore, the job search process will also change if it is endogenized. Mortensen (2003) shows that search intensity is a decreasing function of wages. The workers who earn higher wages search less because the chance for them to climb further up the job ladder is smaller. It is reasonable to believe that workers with different human capital levels also have different incentives to search. Unlike the existing literature, in our model search intensity depends on workers' human capital levels and the rental rates of human capital they currently hold. In this way, the job offer arrival rates differ across worker attributes including human capital levels, rental rates, and experience and age levels.[3] Both of these

[2] We examine post-schooling outcomes and do not allow workers to return to school and/or training programs during unemployment.

[3] Pavan (2008) also allows for more flexibility in search technology, but he assumes the job arrival

factors will contribute to job search and human capital accumulation having different roles over the life cycle and potentially a different contribution to overall earnings growth.

To conduct this study we combine a partial equilibrium search model with a human capital investment model.[4] The search component of the model includes a search effort decision that determines the arrival rate of job offers both on and off the job. As is standard in search models reservation strategies are used to determine optimal transition patterns. In contrast to standard search models, here the reservation strategies depend on the level of human capital as well as current earnings and employment states. In the model human capital is governed by a Ben-Porath investment model where workers spend some of their working time investing in human capital and thus trade off current earnings for future growth in earnings. We chose an investment model for several reasons. First, it is arguably the most common human capital accumulation specification in labor economics. Second, it allows for the human capital accumulation process to be a function of the current rental rate as well as expected future rental rates derived through search. Third, there is evidence that the learning-by-doing model can be rejected by the data in favor of an investment-style model (see, for example, Belley (2011)). Finally, it allows us to contrast our results with the other work in this area that assumes a learning-by-doing human capital accumulation process.

In an attempt to better fit the transition data we augment the model with unobserved heterogeneity in the search parameters (see Liu (2009) for details). We then estimate the model using indirect inference. Through Monte Carlo simulations of the estimation procedure we discovered that the finite-sample properties of the structural parameter estimates rely on how much transition information, including unemployment-to-job and job-to-job transitions, and earnings information are available over the full life cycle. The Monte Carlo exercises show that the estimates using information from partial histories (e.g. the first half of the life cycle) are less precise than those using the full life cycle.[5] The Monte Carlo exercises also show that augmenting early career histories from another data source, especially one with information on job-to-job transitions and earnings from the second half of the life cycle, improves the precision of the parameter estimates. This is because earnings and transitions for older workers provide information for identifying search parameters due to limited human capital investment by older workers. Thus, we estimate the models using a relatively homogeneous cohort from the 1979 National Longitudinal Survey

rates are explicit functions of a series of individual observable and unobservable characteristics, rather than governed by a fundamental underlying mechanism.

[4]We develop a finite-horizon model with a fixed retirement date. This makes all of the decision rules non-stationary and renders solving for the general equilibrium rental rate distribution very difficult. To our knowledge such a general equilibrium model has yet to be solved.

[5]Yamaguchi (2010) and Pavan (2008) are two examples that estimate their models using the NLSY and therefore only the first half of the life cycle.

of Youth (NLSY), with the help of additional information from all ages in the Survey of Income and Program Participation (SIPP).

Based on the estimates from the model with unobserved search heterogeneity, the interactions between human capital accumulation and job search are well supported by the data. Because of job search, on average, workers invest more in human capital throughout the life cycle: 56% more at the beginning of the life cycle than without job search. Because of human capital accumulation, on average, workers reduce their reservation rates while unemployed throughout the life cycle to less than half the reservation rates without human capital accumulation. Furthermore, counterfactual experiments show that a search model without human capital accumulation can generate around 46% of the total earnings growth, while a pure human capital model can generate around 31% of the total earnings growth. The remaining 23% is due to the interactions. Over the life cycle the strength of the components differs with job search dominating earnings growth earlier in the life cycle while human capital accumulation dominates later in the life cycle. In comparison to the rest of the decomposition literature, our results highlight two important findings. First, endogenizing both components yields a substantial role for the interaction effects of each component on the other. Second, modeling search heterogeneity results not only in a better fit of the data, but also a reversal of the ordering of which component plays a larger role.[6]

The rest of the paper is organized as follows. The benchmark model is presented in Section 2. Section 3 discusses the identification and estimation strategies. Details on sample selection and construction of labor market histories are presented in Section 4. Section 5 discusses estimation results and model fit, while Section 6 simulates individual behavior and conducts counterfactual experiments that examine the interactions and quantify the relative contributions of each mechanism to life cycle earnings growth. Section 7 concludes.

2 Model

2.1 The Environment

The model is built in the spirit of a Christensen et al. (2005) search model and a Ben-Porath (1967) human capital production model. Workers enter the labor market unemployed at period 1 and remain in the market until period T when they retire. They maximize their expected earnings over T periods in the labor market by choosing how much market time to invest in human capital and how much effort to spend on

[6] While our findings are consistent with Bagger et al. (2011) in that search overall plays a more dominant role in explaining earnings growth over the life cycle, our results differ from theirs in that we find search is the dominant factor early in the life cycle, not human capital.

search. At each period, they can be either unemployed or employed. They may transit between unemployment and employment as well as from job to job. Workers face a non-degenerate distribution of the rental rate of human capital, $F(R)$, which is log-normally distributed. That is, $\ln(R) \sim N(\mu, \sigma^2)$. Time is discrete. Workers discount the future at a rate β.

2.2 Human Capital Production Technology

Workers are endowed with an initial stock of human capital, h_0, when they enter the labor market. Human capital is assumed to be homogeneous and transferable across jobs. Workers can only invest in human capital while on the job, and thus human capital refers to skills that workers can only acquire through working. Following Heckman et al. (1998), human capital does not depreciate.

Assume a simplified Ben-Porath human capital production function $Q(h, i)$, where h is the current human capital stock and i is the fraction of market time allocated to human capital investment. Assume the production function $Q(\cdot, \cdot)$ is concave in both h and i and takes the following specification

$$Q(h, i) = a(hi)^{\alpha},$$

where $0 < \alpha < 1$ is a curvature parameter and $a > 0$ is a scale parameter which represents learning ability. We assume learning ability is constant over time. Hence the law of motion for human capital for employed workers at period t is

$$h_{t+1} = h_t + a(h_t i_t)^{\alpha}.$$

2.3 Search Technology

Job offer arrival rates depend on workers' search effort. Following Mortensen (2003) and Christensen et al. (2005) denote $\lambda(s)$ as the job offer arrival rate, an increasing and concave function of search effort s with a boundary condition $\lambda(0) = 0$. Assume a linear production function for the job offer arrival rate, i.e. $\lambda(s) = \lambda s$, where λ is a search efficiency parameter.[7] Let $c(s)$ be the search cost function, increasing, strictly convex and twice differentiable, with boundary condition $c(0) = c'_{s \longrightarrow 0} = 0$. The search cost function is assumed to take the following power form

$$c(s) = \frac{c_0 s^{1+\gamma}}{1+\gamma},$$

where $c_0 > 0$ is a scale parameter and $1 + \gamma$ ($\gamma > 0$) is the elasticity of search cost with respect to search effort. Here the search cost refers to the pecuniary disutility associated with job search, not the opportunity cost of market time.

[7]Following Liu (2009) we will let λ vary by type in the estimation in order to fit the duration and transition data better. However, here we suppress the type notation for convenience.

2.4 Worker's Problem

The state variables upon which workers make decisions include the employment state, the current stock of human capital, and the current rental rate. Let $U_t(h)$ denote the value of being unemployed at period t and with human capital h. Let $V_t(h, R)$ be the value of working at a firm offering a rental rate R at period t with human capital h. The worker's problem can be characterized recursively by two Bellman equations. The Bellman equation for an unemployed worker is

$$\begin{aligned} U_t(h) \quad = & \quad \max_{s_t^0} bh - c(s_t^0) + \beta\lambda s_t^0 \int_0^\infty \max\{U_{t+1}(h), V_{t+1}(h, R)\} dF(R) \\ & \quad + \beta(1 - \lambda s_t^0) U_{t+1}(h) \\ s.t & \\ & \quad 0 \leq \lambda s_t^0 \leq 1 \end{aligned} \tag{1}$$

At period t, an unemployed worker receives some amount of compensation, bh, which is proportional to his stock of human capital in that period. It may include unemployment benefits as well as other forms of income workers receive while unemployed. The assumption that the unemployment compensation is proportional to worker's human capital makes the model easier to solve. Furthermore, it is not hard to justify if unemployed workers engage in home production or other forms of non-market activities which presumably depend on productivity or if unemployment benefits are a function of past wages.[8] We assume b, the replacement rate for the unemployed, is constant over time and independent of h and r.[9] At the beginning of period t, given human capital, h, the worker must decide how much effort, s_t^0, to expend on job search which in turn determines the job offer arrival rate at the end of period t. At the end of period t with probability λs_t^0, the worker receives a job offer R from the offer distribution $F(R)$. The worker has to immediately decide whether to accept that offer by comparing the value of working at period $t+1$ to the value of staying unemployed at period $t+1$. With probability $1 - \lambda s_t^0$, the worker does not receive an offer and remains unemployed in period $t+1$.

The Bellman equation for an employed worker who works at a firm offering R

[8] Similar settings can be found in Postel-Vinay and Robin (2002) and Burdett et al. (2011).

[9] These assumptions are useful for identification and for keeping the state space manageable.

with human capital h at period t is

$$\begin{aligned} V_t(h,R) \quad = \quad & \max_{\{s_t^1, i_t\}} Rh(1-i_t) - c(s_t^1) + \beta(1-\delta)(1-\lambda s_t^1)\max\{V_{t+1}(h',R), U_{t+1}(h')\} \\ & +\beta(1-\delta)\lambda s_t^1 \int_0^\infty \max\{V_{t+1}(h',R'), V_{t+1}(h',R), U_{t+1}(h')\} dF(R') \\ & +\beta\delta U_{t+1}(h') \\ s.t \quad & \\ & 0 \leq i_t \leq 1, \\ & 0 \leq \lambda s_t^1 \leq 1 \\ & h' = h + a(hi_t)^\alpha. \end{aligned} \tag{2}$$

At the beginning of period t given human capital stock h and rental rate R, an employed worker has to decide not only how much effort s_t^1 to spend searching for a better job but also how much time i_t to invest in human capital. Earnings for this period depend on how much time is devoted to market production, i.e. $Rh(1-i_t)$. Search activity is assumed to not affect earnings in the current period because it incurs only monetary costs, not opportunity costs of market time. On the one hand, this serves as an identification assumption that allows for the identification of the human capital production function using within job earnings variation as such variation is only driven by human capital investment under the current settings. On the other hand, this makes search costs independent of the level of human capital. If search costs also included the opportunity costs of market time, workers with more human capital would exert less search effort. At the end of period t, the job can be destroyed with probability δ in which case the worker returns to unemployment in period $t+1$. With probability $(1-\delta)\lambda s_t^1$, the job is not destroyed and the worker receives a new job offer R' at the end of period t. The worker then must decide whether to accept the new job offer R' by comparing the value of working at the new job in period $t+1$ to that of staying with the current job in period $t+1$ with the new human capital h'. The worker may also decide with the new human capital level h' to transition to unemployment if that state now dominates. With probability $(1-\delta)(1-\lambda s_t^1)$, the job is not destroyed and the worker receives no offers and decides between staying with the current job in period $t+1$ and transitioning to unemployment. Human capital grows due to investment and human capital in period $t+1$ is determined by the law of motion.

It can be shown from backward induction that $U_t(h)$ is increasing in h and $V_t(h,R)$ is increasing in both h and R. Given these properties of the value functions, unemployed workers adopt the following reservation rental rate strategy: only offers that are at least as good as the reservation rental rate, denoted by $\phi_t(h)$ and determined by $U_t(h) = V_t(h, \phi_t(h))$, are accepted. Using the reservation rental rate strategies, equation (1) can be simplified as follows.

$$
\begin{aligned}
U_t(h) \quad &= \quad \max_{s_t^0} bh - c(s_t^0) + \beta\lambda s_t^0 \int_{\phi_{t+1}(h)}^{\infty} (V_{t+1}(h,R) - U_{t+1}(h))\, dF(R) \\
&\qquad +\beta U_{t+1}(h) \\
&s.t. \\
&\qquad 0 \leq \lambda s_t^0 \leq 1. \qquad (3)
\end{aligned}
$$

For employed workers, the reservation rental rate, at which workers are indifferent between accepting the new offer and staying with the current job, is the current rental rate, since human capital is general and transferable between jobs. Allowing for endogenous quits to unemployment from employment complicates the transitions in that a worker now has to decide, given the new level of human capital, whether to remain at the current job or switch to unemployment or accept a new job, if offered. These decisions depend on the relationship between R' (the new offer if available), R, and $\phi_{t+1}(h')$. For a worker whose current rental rate R is higher than the updated unemployment reservation rental rates $\phi_{t+1}(h')$, the decision is the same as the case when endogenous quits to unemployment are not allowed. In this case, the worker's problem can be simplified to

$$
\begin{aligned}
V_t(h,R) \quad &= \quad \max_{\{s_t^1, i_t\}} Rh(1-i_t) - c(s_t^1) + \beta(1-\delta)V_{t+1}(h',R) + \beta\delta U_{t+1}(h') \\
&\qquad +\beta(1-\delta)\lambda s_t^1 \int_{R}^{\infty} (V_{t+1}(h',R') - V_{t+1}(h',R))\, dF(R') \\
&s.t. \\
&\qquad 0 \leq i_t \leq 1, \\
&\qquad 0 \leq \lambda s_t^1 \leq 1 \\
&\qquad h' = h + a(hi_t)^{\alpha}. \qquad (4)
\end{aligned}
$$

For a worker whose current rental rate R is lower than $\phi_{t+1}(h')$, the decision will be to quit to unemployment unless they receive a new job offer such that $R' > \phi_{t+1}(h')$, in which case they will accept the new offer and remain employed. That is,

$$
\begin{aligned}
V_t(h,R) \quad &= \quad \max_{\{s_t^1, i_t\}} Rh(1-i_t) - c(s_t^1) + \beta U_{t+1}(h') \qquad (5) \\
&\qquad +\beta(1-\delta)\lambda s_t^1 \int_{\phi_{t+1}(h')}^{\infty} (V_{t+1}(h',R') - U_{t+1}(h'))\, dF(R').
\end{aligned}
$$

Endogenous quits to unemployment generally do not arise in standard search models, because the environment is stationary. However, in our model, the finite working lifetime makes the model non-stationary and under many parameter specifications the reservation rental rate increases over time as search effort and human capital investment returns diminish. This is especially true as one gets closer to the last period where for all values of h the reservation rental rate is equal to b.

2.5 Analysis of Model Properties

Given its complexity, the model is analytically intractable and hence is solved numerically.[10] Without loss of generality we assume that at period $T+1$, $U_{T+1} = V_{T+1} = 0$. Therefore, for period T, $U_T(h) = bh$, $V_T(h, R) = Rh$, and $\phi_T(h) = b$ since neither search nor human capital investment takes place. The policy functions and value functions for periods prior to T are solved by backward induction based on the following three first order conditions:[11]

$$c'(s_t^0) = \beta\lambda \int_{\phi_{t+1}(h)}^{\infty} (V_{t+1}(h, R) - U_{t+1}(h))\, dF(R), \tag{6}$$

$$c'(s_t^1) = \beta(1-\delta)\lambda \int_{R}^{\infty} (V_{t+1}(h', R') - V_{t+1}(h', R))\, dF(R'), \tag{7}$$

and

$$\begin{aligned} Rh \quad = \quad & \beta \frac{\partial h'}{\partial i_t} \left(\delta \frac{\partial U_{t+1}(h')}{\partial h'} + (1-\delta) \frac{\partial V_{t+1}(h', R)}{\partial h'} \right. \\ & \left. + (1-\delta)\lambda s_t^1 \int_R^{\infty} \left(\frac{\partial V_{t+1}(h', R')}{\partial h'} - \frac{\partial V_{t+1}(h', R)}{\partial h'} \right) dF(R') \right). \end{aligned} \tag{8}$$

Search intensity for unemployed workers s_t^0 increases in h, because the marginal returns to search, the RHS of equation (6), are higher for workers with more human capital. The interactions between human capital investment and job search are such that with human capital accumulation unemployed workers, on average, spend more effort on search and reduce their reservation rental rates. The intuition is simple. Human capital accumulation makes employment relatively more attractive compared to unemployment. On the one hand, workers receive constant compensation bh and see no growth in human capital while unemployed. On the other hand, they may augment their human capital and locate better outside offers while employed. It is also important that the search technology and search costs are the same for the employed and the unemployed. This encourages unemployed workers to exit unemployment as quickly as possible by searching more intensively and lowering their reservation rental rates. Hence s_t^0 is higher and the reservation rental rate $\phi_{t+1}(h)$ is lower than without human capital growth.

Search intensity for employed workers s_t^1 increases in h because search is more valuable for individuals with more human capital. It decreases in R because a worker with a higher R is less likely to move up the job ladder and more likely to stay with the

[10] We have solved a simplified 3-period model analytically. Under some sufficient conditions, we were able to show that s^0 is increasing in h, s^1 is increasing in h and decreasing in R, and h' is increasing in h and decreasing in R.

[11] For simplicity, we present and discuss only the case where the current rental rate is higher than the reservation rental rates and thus no voluntary exits to unemployment occur.

current job. Therefore the return to search, the RHS of equation (7), is decreasing in R. The on-the-job search intensity with human capital growth is higher than without, since the marginal return to search is higher than it would be with no human capital growth.

As in the human capital literature, human capital investment i_t is decreasing in h due to the concavity of the human capital production function. However, unlike the pure human capital literature, i_t is now a function of the rental rate because of job search. In particular, i_t is decreasing in R, because the marginal returns to investment now include the returns to search. That is, the marginal returns to investment, the RHS of equation (8), not only include the marginal returns if workers stay with the same job as is the case without search, but also include the marginal returns if workers transition due to search. The higher R is the more likely workers stay with the same job and the less likely they switch to a better job decreasing the incentives to invest. In addition, the possibility of job destruction makes investing in human capital risky. Both of these factors lead to declining investment in human capital as the rental rate increases. However, conditional on R, workers invest more in human capital in the presence of job search than without as they can foresee their rental rates increasing in the future through job search, the third term on the RHS of equation (8).

3 Estimation

In order to better fit the duration and transition data, we follow Liu (2009) and allow for unobserved heterogeneity in the arrival rate parameter λ.[12] In particular, we specify two types of workers such that $\lambda_1 \leq \lambda_2$ with the fraction of type 1 workers equal to p. Thus, the parameters of interest include seven parameters related to search frictions (λ_1, λ_2, δ, b, c_0, γ, and p), two human capital production function parameters (a and α), the initial human capital level (h_0), and two rental rate distribution parameters (μ and σ). Here we invoke common normalizations for identification purposes. With regard to the search parameters Christensen et al. (2005) show that λ_i, c_0 and γ cannot be separately identified since search intensity is not observable. As is commonly done, we normalize c_0 to 1. It is also well known in the human capital literature that one cannot separately identify the level of human capital from the rental rate. This is mainly because we only observe the product of human capital and the rental rate. In the usual case of a single rental rate, the rental rate is normalized to some particular value so that it is possible to interpret human capital in a pecuniary sense. With the integration of job search and human capital accumulation such a normalization does not resolve the issue. It is possible to achieve identification in

[12] Liu (2009) modified a similar model along a number of possible dimensions to achieve a better fit to the duration and transition data. He determined that heterogeneity in λ led to the best improvement. Subsequently we have analyzed other extensions including allowing for heterogeneity in both λ and δ and again have settled on heterogeneity in λ.

our setting by normalizing the initial human capital level and we do so by setting h_0 to 100. In this way, the rental rate distribution parameters can be estimated with available data. We also set an upper limit on the rental rate distribution equal to 30. This value yields weekly earnings at the top of the distribution around 3000, similar to what we find in the SIPP data.[13] Finally, the discount factor β is set to .99. This follows the convention in the literature that $\beta = 1/(1+r)$ with the interest rate r set equal to roughly 1% per quarter which amounts to a real annual interest rate of 4%.

The rest of the parameters are estimated via indirect inference (Gourieroux et al. (1993)). Indirect inference is a generalization of the method of simulated moments. It is particularly useful when a model is not analytically tractable. The main idea is to find a set of structural parameters that minimize the distance between a set of moments from the real data and the model-predicted counterparts of these moments based on simulated data from the structural model. The set of moments that are matched can be viewed as a set of auxiliary parameters from a set of auxiliary models. These auxiliary models can be structural or reduced form and they should capture the main features of the original structural model.

3.1 Auxiliary Model

One of the key issues in using indirect inference is to find moments or auxiliary models that help identify all of the parameters. From the search literature it is known that the search friction parameters can be identified through transition information including transitions between unemployment and employment and job-to-job transitions. Recall in the model that the hazard rate out of an unemployment spell at period t for a type i worker is $\lambda_i s_t^0(h_t)(1 - F(\phi_t(h_t)))$ and the job-to-job hazard rate at a firm offering R is equal to $(1-\delta)\lambda_i s_t^1(h_t, R)(1-F(R))$, assuming $R \geq \phi_{t+1}(h_{t+1})$. Examining how outcomes of unemployment-to-employment transitions and job-to-job transitions respond to variations in h and R can help reveal the underlying search parameters, λ_i and γ. Although h and R are not observable in data, they can be approximated by work experience, job tenure, and earnings. Finally, duration dependence in the unemployment-to-employment transitions helps to separately identify λ_1 and λ_2 as well as p. Thus we regress binary outcomes of unemployment-to-employment transitions against actual work experience and unemployment duration, and binary outcomes of job-to-job transitions against actual work experience, job tenure, and earnings to reveal the underlying relationship between search intensity and h and R.

Let $Y_{i,k,t}$ be a binary choice variable for individual i during unemployment spell k at period t, with 1 for exit and 0 for otherwise. Let $x_{i,t}$ be the actual work experience,

[13]If we do not impose this limit, for high values of b the estimates can yield a low mean, high variance rental rate distribution such that the offer rejection rate out of unemployment is extremely high and on-the-job search yields earnings at the top of the distribution more than double that found in the data.

i.e. total labor market experience net of unemployment durations, of individual i at period t. Denote $udur_{i,k,t}$ as the cumulative duration for individual i's k^{th} unemployment spell at period t. Then

$$Y_{i,k,t} = \beta_0 + \beta_1 x_{i,t} + \beta_2 x_{i,t}^2 + \beta_3 udur_{i,k,t} + \beta_4 udur_{i,k,t}^2 + u_{i,k,t}, \tag{9}$$

where $u_{i,k,t}$ is an error term. Similarly, for job-to-job transitions, let $Y_{i,j,t}$ be a binary choice variable for job spell j at period t of individual i, with 1 for a job-to-job transition and 0 otherwise. Let $T_{i,j,t}$ be the tenure at period t for job j, $w_{i,j,t}$ be earnings on job j at period t for individual i.

$$Y_{i,j,t} = \beta_5 + \beta_6 x_{i,t} + \beta_7 x_{i,t}^2 + \beta_8 T_{i,j,t} + \beta_9 T_{i,j,t}^2 + \beta_{10} w_{i,j,t} + \beta_{11} w_{i,j,t}^2 + u_{i,j,t}, \tag{10}$$

where $u_{i,j,t}$ is again an error term.

Earnings growth in the model is a result of both human capital accumulation and job switching. Nevertheless, on the same job, earnings grow solely due to human capital accumulation. Hence regressing within-job earnings growth against actual experience and job tenure helps identify the human capital production function parameters, a and α. Let $\ln w_{i,j,t}$ be log earnings of individual i on job j at period t. Define $\Delta \ln w_{i,j,t} = \ln w_{i,j,t} - \ln w_{i,j,t-1}$.

$$\Delta \ln w_{i,j,t} = \beta_{12} + \beta_{13} x_{i,t} + \beta_{14} x_{i,t}^2 + \beta_{15} T_{i,j,t} + \beta_{16} T_{i,j,t}^2 + \epsilon_{i,j,t}, \tag{11}$$

where $\epsilon_{i,j,t}$ is the corresponding error term.

A Mincerian earnings regression helps identify the rental rate distribution parameters μ and σ. In addition to actual experience and job tenure, we also include djj in the regression, a job-to-job transition indicator with value equal to 1 if the state prior to the current job is another job and 0 if not. The model predicts that, on average, earnings following job-to-job transitions are higher. Let $\ln w_{i,j,t}$ be log earnings at period t for individual i on job j.

$$\ln w_{i,j,t} = \beta_{17} + \beta_{18} x_{i,t} + \beta_{19} x_{i,t}^2 + \beta_{20} T_{i,j,t} + \beta_{21} T_{i,j,t}^2 + \beta_{22} djj_{i,j,t} + \nu_{i,j,t}. \tag{12}$$

Given the assumption of a common level of initial human capital, variations in initial earnings on first jobs and job-to-job transitions following first jobs come solely from variation in R. Such information helps identify the variance of the rental rate distribution, σ. The mean of initial earnings of first jobs also helps to identify the mean of the distribution, μ, given that h_0 is normalized to 100. Let $\ln w_{i,1}$ and $Y_{i,1}$ be the logarithm of earnings at the start of the first job and the first job-to-job transition of individual i on the first job, respectively. Let $jdur_{i,1}$ be the total duration of the first job for individual i. Following the above argument, we include in the auxiliary model the mean and standard deviation of initial earnings on the first jobs, $\overline{\ln w_{i,1}}$ and $\sigma_{\ln w_{i,1}}$, and coefficients from the following regression:

$$Y_{i,1} = \beta_{23} + \beta_{24} jdur_{i,1} + \beta_{25} jdur_{i,1}^2 + \varepsilon_i. \tag{13}$$

The job destruction rate δ is assumed to be the same for everyone and constant over time. In the auxiliary model it is identified from data on the fraction of workers in the NLSY who exit employment in each period since in the model this value is the sum of δ and the endogenous exit rate from employment implied by the other parameter estimates. The replacement rate for unemployed workers b affects the reservation rental rates and is equal to the reservation rental rate at period T. Hence minimum earnings levels at period T, $\underline{w}_T$, particularly amongst those who recently transitioned from unemployment can help identify b.

3.2 Monte Carlo Exercise

To confirm if the auxiliary model proposed above contains enough information to identify all the model parameters, we conducted a small Monte Carlo exercise which is described in Appendix A. The results from the Monte Carlo exercise revealed that the estimates using the proposed auxiliary model were very close to the true values indicating that the auxiliary model can recover the true parameters. The estimates were also very precise if all the information used to calculate the moments is available over the full life cycle. However, the estimates are much nosier if only a subset of the life cycle is observed. Finally, the Monte Carlo exercises revealed that the precision of the estimates could be improved if the auxiliary model was augmented with an additional data source that contains information on the full life cycle.

Since the primary choice of data set for this study, the NLSY, does not cover the full working life of the sample participants,[14] we chose to augment the information in the NLSY with information covering the full life cycle from the 1996 wave of the SIPP.[15] In order to provide information on the full life cycle, we constructed synthetic profiles of job-to-job transitions and earnings over 40 years in the SIPP and included SIPP versions of equations (10) and (12) in the auxiliary model. One concern with the synthetic cohorts from the SIPP is that they may have faced different parameter values than the NLSY cohort. In the observed data the shape of the overall profiles of job-to-job transitions and earnings are quite similar for the age range that overlaps in the NLSY and the SIPP. However, the intercept terms are different. Thus, to control for potential cohort effects introduced by combining the NLSY and the SIPP, we do not include the intercept terms from equations (10) and (12) for the SIPP in the indirect inference estimation. A second concern with the SIPP entails the small sample size of older workers who transition from unemployment to employment, the sample used in the Monte Carlo exercises to identify b. In addition, the SIPP is known to underreport wages (Abowd and Stinson (2011)). Thus, instead of estimating b within the indirect inference estimation procedure, we choose the value of b by comparing the implied earnings at the end of the life cycle and those in the SIPP data for workers who

[14] The majority of individuals in our final sample only have 20 years of labor market history.

[15] The SIPP is a representative panel with a relatively short duration of only 4 years.

are within one year and five years of age 65. Our preferred value of b is 1.8 which results in a smallest earnings level of 120 in the last 5 years and 137 in the last year of employment.[16]

In summary, our final auxiliary model uses a combination of data from the NLSY covering the first 20 years of the life cycle and from the SIPP covering the full 40 years of the life cycle. More formally, denote θ as the set of parameters of interest that need to be estimated. That is, $\theta = \{\lambda_1, \lambda_2, \delta, \gamma, a, \alpha, \mu, \sigma, p\}$. Denote ρ as the vector of auxiliary parameters, whose consistent estimator based on the real data is $\hat{\rho}$. Here ρ includes all the regression coefficients from equations (9) to (13) for the first 20 years, the mean and standard deviation of initial earnings on the first jobs, the fraction of employed workers making job to unemployment transitions in the first 20 years, and the slope coefficients from the following two regressions for the full 40 years of the life cycle,

$$Y_{i,j,t} = \beta_{26} + \beta_{27} ex_{i,t} + \beta_{28} ex_{i,t}^2 + u_{i,j,t}, \tag{14}$$

and

$$\ln w_{i,j,t} = \beta_{29} + \beta_{30} ex_{i,t} + \beta_{31} ex_{i,t}^2 + \nu_{i,j,t}. \tag{15}$$

where $ex_{i,t}$ is the potential experience of individual i at period t. Let $\hat{\rho}(\theta)_s$ be the consistent estimator of ρ from the artificial data generated from one simulation of the structural model, indexed by s. Let $\hat{\rho}(\theta)$ be the average of S simulations, $\hat{\rho}(\theta) = (1/S)\Sigma_{s=1}^{S} \hat{\rho}(\theta)_s$. Then the consistent estimator of θ, via indirect inference, is given by

$$\hat{\theta} = \arg\min(\hat{\rho}(\theta) - \hat{\rho})' W^* (\hat{\rho}(\theta) - \hat{\rho}), \tag{16}$$

where W^* is the optimal weighting matrix, which is equal to the inverse of the covariance matrix of $\hat{\rho}$, $Var(\hat{\rho})^{-1}$. The minimization is implemented using simulated annealing (Goffe et al. (1994)) and the optimal weighting matrix is obtained through bootstrapping.

4 Data

As discussed in the previous section, the NLSY and the SIPP are used in the estimation. The NLSY consists of 12,686 individuals who were 14 to 21 years old as of January 1979. It contains a nationally representative core random sample, an over-sample of blacks and Hispanics, and a special military over-sample. Respondents were interviewed annually since 1979 until 1994 and once every two years after 1994. Detailed information on employment and schooling was collected. For this analysis,

[16]The lowest 4 earnings values in the SIPP data are 78, 105, 119 and 125 for workers within 5 years of age 65 and 119, 146, 146 and 167 for workers within one year of age 65. The sample sizes are 1738 and 248, respectively.

only the core sample is used. As for the SIPP, the 1996 panel is used which covers 4 years. The SIPP sample is a multistage-stratified sample of the U.S. civilian non-institutionalized population. All household members 15 years old and over are interviewed by self-response or proxy response every 4 months. Core information on labor force status, program participation and income for the past 4 months is asked at each interview. Both data sets provide instruments with which jobs can be linked across interviews and thus individual labor market histories can be constructed.

4.1 Sample Selection

In both data sets, only white males who are high school graduates and do not pursue further schooling are selected to maintain homogeneity. Those who had ever been self-employed, family workers, served in military, or retired are also excluded from both samples. In the NLSY, we select only those who graduated from high school after 1978, since constructing employment histories prior to 1978 is not possible in the NLSY, and before 1984 in order to have more homogeneous cohorts and longer labor market histories. In the SIPP, we restrict the sample to those who were high school graduates as of January 1996.

In both samples, a job is defined as an employment relationship that consists of at least 35 hours a week and lasts longer than 4 weeks.[17] In the NLSY, these full-time jobs have to start within three years after high school graduation to guarantee the school-to-work transition.[18] If the first full-time job happens to surround the graduation date, it is used as the first spell only if it is held at least 2 months after graduation. This eliminates temporary or summer jobs held while still in school. To deal with overlapping jobs, those jobs that are covered entirely by other longer jobs are dropped. For those jobs that only overlap in part, the starting dates of the later jobs are replaced with the stopping dates of the earlier jobs. In both samples, if a job is indicated as still ongoing at the last interview, the job is right-censored.

Weekly earnings are used and converted to 2000 dollars in both samples. In the NLSY, respondents are asked the time unit of the rate of pay and the corresponding rate of pay. If an individual is not paid weekly, the rate of pay is then converted to weekly earnings using hours information. In the SIPP, monthly earnings are recorded. Hence, weekly earnings are then equal to monthly earnings divided by actual weeks worked for that particular month. In both samples, earnings are trimmed 1% at the top and bottom of the distributions.

[17]The focus on full-time jobs is standard in the literature. See, for example, Bowlus et al. (2001), Eckstein and Wolpin (1995), Wolpin (1992), Yamaguchi (2010), Topel and Ward (1992), and Rendon (2006).

[18]See Bowlus et al. (2001) for details.

4.2 Quarterly Histories

Since the model period is a quarter (13 weeks), quarterly labor market histories since high school graduation are constructed for the two samples. The quarterly histories are constructed according to the following rules. First, the calendar quarter that contains the high school graduation date is set as the first quarter in the labor market.[19] Second, employment states are determined based on the major activity occurring during a particular calendar quarter.[20] A worker is classified as employed during a quarter if he works at a legitimate job based on the aforementioned definition the majority of that quarter, i.e. greater than 7 weeks. Otherwise, he is classified as unemployed during that quarter. Third, the job of the quarter is defined as the one that a worker stays with the longest during that quarter, given he is employed during that quarter. Earnings on this job during that quarter is then defined as the earnings for the quarter. Fourth, the quarterly transitions are determined based on the employment states and jobs held during two consecutive quarters. A worker makes an unemployment-to-job transition if he is unemployed in the current quarter and employed in the next quarter. A worker makes a job-to-job transition if he changes jobs between two quarters.

The final sample consists of 446 individuals from the NLSY with 2424 full-time jobs and 1395 unemployment spells in total, and 5109 individuals from the SIPP with 7293 full-time jobs and 1254 unemployment spells. Due to its longer panel, the right-censoring rate in the NLSY sample is low: 13% and 11%, respectively, for unemployment and job spells. However the censoring rate is high in the SIPP sample due to its shorter panel: 29% and 68% for unemployment and job spells, respectively. Based on the quarterly histories constructed from the NLSY, a typical high school graduate holds 5.4 full-time jobs over the first 20 years and makes 2.7 job-to-job transitions and 2.1 job-to-unemployment transitions. An unemployment spell on average lasts for 5.7 quarters[21] and a job spell lasts for 13 quarters.

Table 1 shows several quarterly statistics for 4 potential experience groups for the NLSY sample and 4 additional groups for the SIPP sample. Full-time work experience increases from 6.7 quarters over the first 5 years to 51 quarters if one has been in the labor market for 16 to 20 years. Job seniority increases from 4.2 quarters over the first 5 years to 23 quarters if one has been in the market for 16 to 20 years. As experience and job seniority increase, average weekly earnings increase from $445 to $685 over the same period of time. Average weekly earnings grow at a decreasing rate. From year 5 to year 10, average weekly earnings increases by $124, then $69 from years 10

[19] Similar settings can be found in Wolpin (1992) and Eckstein and Wolpin (1995).

[20] There are generally two ways to construct quarterly histories. One is to use the information at the first week of a particular quarter. The other is to use the major activity of a particular quarter. Yamaguchi (2010) and Rendon (2006) use the former, while Topel and Ward (1992) and Wolpin (1992) use the latter.

[21] By construction, an unemployment spell may include jobs that do not qualify as full-time jobs.

Table 1: Quarterly Statistics

	NLSY			
Mean	1-5 Years	6-10 Years	11-15 Years	16-20 Years
Actual Experience (quarters)	6.74	23.12	40.12	57.08
	(5.41)	(8.45)	(11.49)	(15.13)
Job Tenure (quarters)	4.22	10.63	16.72	23.07
	(4.76)	(9.96)	(15.81)	(22.14)
Weekly Earnings	444.51	569.05	638.33	685.38
	(203.33)	(254.61)	(262.32)	(293.56)
Quarterly Within-Job Earnings Growth	0.019	0.008	0.004	0.003
	(0.106)	(0.080)	(0.067)	(0.056)
Quarterly Between-Job Earnings Growth	0.035	0.032	0.042	0.009
	(0.261)	(0.229)	(0.207)	(0.167)
Fraction of Employed Workers who Transition	0.063	0.049	0.033	0.028
from Job-to-Job (per quarter)	(0.243)	(0.216)	(0.178)	(0.164)
Fraction of Unemployed Workers who	0.214	0.166	0.118	0.070
Transition to a Job (per quarter)	(0.411)	(0.373)	(0.323)	(0.255)
	SIPP			
Mean	21-25 Years	26-30 Years	31-35 Years	36-40 Years
Weekly Earnings	686.60	675.58	701.12	750.80
	(307.87)	(308.71)	(335.81)	(349.21)
Quarterly Within-Job Earnings Growth	0.000	0.001	-0.000	0.001
	(0.230)	(0.228)	(0.218)	(0.225)
Quarterly Between-Job Earnings Growth	0.029	0.089	0.055	-0.083
	(0.440)	(0.623)	(0.554)	(0.597)
Fraction of Employed Workers who Transition	0.026	0.021	0.020	0.013
from Job-to-Job (per quarter)	(0.159)	(0.143)	(0.141)	(0.114)

to 15 and $47 from years 15 to 20. From the SIPP data we show statistics for older workers who are missing from the NLSY panel. Average weekly earnings in the SIPP for those who have been in the labor market for 21 to 25 years is very similar to that in the NLSY for those in the market for 16-20 years.[22] The SIPP does show higher average earnings for older workers with an average of $751 for worker who have been in the market 36 to 40 years.

In terms of earnings growth we present two statistics: average within-job earnings growth across two quarters for those staying with the same job and average between-job earnings growth across two quarters for those changing jobs. On average, a high school graduate can expect earnings growth of 2% per quarter on the job over the first 5 years. This amounts to about 8% per year. This growth declines over time, down to 0.3% per quarter if one has been in the market for 16 to 20 years. After 20 years the SIPP data reveal almost no within-job earnings growth. Job switching results in earnings growth of 3.5% per quarter over the first 5 years, which is twice as high as the growth on the job over the same period of time. The between-job earnings growth does not decrease as much as the within-job earnings growth in the NLSY and the SIPP data show very noisy patterns of gains and losses toward the end of the life cycle.

In terms of transitions across states the NLSY reveals that the likelihood of making a job-to-job transition declines as experience levels increase with the SIPP data showing a leveling off. With respect to transitions out of unemployment the NLSY sample indicates a quite sharp decline as experience levels increase with the SIPP showing a flat pattern.[23] The discrepancies between the NLSY and the SIPP in some of the transition information (earnings growth and unemployment to job transitions especially) are behind our decision to only include information on these patterns in the data for the first 20 years, i.e. only use the NLSY data. The exclusion of this information in the auxiliary model is unlikely to have a big impact on the parameter estimates as shown in the previous Monte Carlo exercises. Additional issues encountered during estimation due to the nature of the data and our solutions are discussed in Appendix B.

[22] As noted above the SIPP has a lower intercept for its earnings-potential experience profile than the NLSY.

[23] The fraction of unemployed workers transitioning to a job in the SIPP is somewhat flat over time, ranging from 29% for the first 5 years to 23% for the 30 to 35 years in the labor market.

5 Estimation Results

5.1 Parameter Estimates

The parameter estimates for the estimated model are presented in Table 2. Our preferred specification with b=1.8 is given in the first column. The results show that there is substantial heterogeneity in terms of search efficiency in the data, with 42% being type 1 and 58% type 2. Type 2 workers are almost 5 times more efficient in searching than type 1 workers and hence receive job offers faster conditional on the same search effort. For one unit of search effort the job offer arrival probability is only 2.9% per quarter for type 1 workers, while it is 14.2% for type 2 workers. The average job offer arrival rate among the two types is 9% per quarter. This estimate is larger than those found by other models with endogenous search intensity.[24] The estimate of the search cost curvature parameter γ is 9.16 and is much higher than those found by other studies.[25] This difference is due to the presence of human capital accumulation in our model. Because of human capital accumulation, search intensity is not only a decreasing function of the rental rate but also an increasing function of human capital level. Thus, search effort has to be more costly to maintain the same job offer arrival rate at a given level of observed earnings.[26] In terms of job destruction, δ is estimated to be 0.03 which is the average employment to unemployment exit rate in the NLSY suggesting very little role for endogenous job separations in the model.

Turning to the parameter estimates of the human capital production function we find that the learning ability parameter a is estimated to be 0.24, a value that is much larger than those found in the human capital literature.[27] In contrast, the curvature parameter α is smaller at 0.024 than values found in the human capital literature.[28] In a human capital model, the parameter α governs the shape of age-earnings profile. The higher α is the more time workers invest in human capital in the beginning of the life cycle and hence the more concave the age-earnings profile is. In the human capital literature, a larger α is estimated compared to our model with search heterogeneity. This is because the only way to generate a concave age-earnings profile in the pure human capital model is to have a large α. However, with heterogeneity in the search

[24] Lise (2011) finds that λ is 0.19 per year using the NLSY, implying roughly a job offer arrival probability of 5% per quarter.

[25] Lise (2011) finds that the search cost curvature is 1.17 using the NLSY. Christensen et al. (2005) find the search cost function is very close to a quadratic using Danish data.

[26] Consider search intensity under two observed earnings, $w_1 = rh_1$ and $w_2 = rh_2$ with $h_1 < h_2$. The search intensity at w_1 will be higher than at w_2 in studies with only endogenous search effort. However, search intensity at w_2 will be higher because of higher h_2 in our model. This implies a more costly search in our model to maintain a similar job offer arrival rate.

[27] For example, Heckman et al. (1998) find that a is around 0.08 for high school graduates using the NLSY.

[28] Browning et al. (1999) finds the curvature estimates in the human capital literature range from 0.5 to almost 1.

Table 2: Model Parameter Estimates

	$b = 1.8$	$b = 1.7$	$b = 1.9$
h_0	100	100	100
c	1	1	1
β	0.99	0.99	0.99
λ_1	0.029	0.032	0.040
	(0.002)	(0.003)	(0.003)
λ_2	0.142	0.163	0.185
	(0.008)	(0.012)	(0.011)
p	0.417	0.470	0.417
	(0.028)	(0.047)	(0.034)
γ	9.162	11.875	8.819
	(0.180)	(0.509)	(0.545)
δ	0.030	0.030	0.030
	(0.001)	(0.001)	(0.001)
a	0.236	0.249	0.066
	(0.053)	(0.054)	(0.011)
α	0.024	0.024	0.069
	(0.024)	(0.021)	(0.036)
μ	1.266	1.276	0.955
	(0.013)	(0.012)	(0.018)
σ	0.461	0.452	0.670
	(0.019)	(0.018)	(0.014)

technology, it is not necessary to have a large curvature parameter for the human capital production function because job search per se, especially amongst the type 2 workers, can generate a concave age-earnings profile. The mean of the logarithm of the rental rate is 1.27 and the standard deviation is 0.46. Thus for one unit of human capital, the mean rental rate is about 3.9 per week. The implied rental rate distribution is disperse and skewed to the right with a long right tail.

5.2 Model Fit

Table 3 tabulates the moments used in the estimation and those generated by the model. The model does well in matching the earnings-related moments which include the log earnings regression (equation (12)) and the initial earnings distribution from the NLSY, and the overall earnings profile (equation (15)) from the SIPP. The model also does a reasonable job matching the transition data. Figure 1 illustrates the fit of the model graphically. Much of the decline in the job-to-job transition profiles as seen in the NLSY and the SIPP (parts (c) and (d)) is replicated by the model. Unlike a model with homogeneous search parameters which generates a flat unemployment-to-job transition profile (Liu (2009)), the model with search heterogeneity does generate an initial decline for the unemployment-to-job transition profile (part (e)). However, it misses the higher exit rate out of unemployment for very young workers and the subsequent decline in the exit rate as workers age. For the most part this is due to (1) the very high exit rate for type 2 workers such that mainly type 1 workers remain in unemployment after a few periods and (2) not enough variation over time in the reservation rental rate as in the homogeneous search model. In terms of earnings profiles, the model matches both the NLSY and the SIPP very well.

Note that the coefficient on djj, a dummy variable for job-to-job transitions in the log earnings regression, is much higher in the model than in the data (Table 3). This is because in the model job-to-job transitions only happen when workers receive a better offer. However, this may not be the case in reality. Bowlus and Neumann (2006) document almost 34% of voluntary job changes for job-related reason result in a wage decline, not to mention job changes for non job-related reasons. Finally, the model generates smaller within-job earnings growth compared to the data (Table 3). This appears to be a consequence of adding heterogenous job search to the model. Fitting the job-to-job transitions well results in a model that can produce a concave earnings profile with a reasonable amount of earnings growth over the life cycle. Less human capital investment is then needed to fit the overall earnings profile. This results in lower estimates for the human capital parameters and subsequently lower on-the-job earnings growth.[29]

5.3 Sensitivity to Choice of b

In Table 2 we also present the estimation results when b is set equal to a lower value of 1.7 (column 2) and a higher value of 1.9 (column 3). We first note that the parameter estimates with b=1.7 are very close to those when b=1.8. This is true for all values of b lower than 1.7, because for these specifications the offer rejection rate is essentially zero. Once the value of b is low enough such that workers accept virtually all offers, then the estimates of the other parameters are fairly stable across different values of b. For example, the search parameters are stable because the rejection rate of offers does not vary. Hence, the estimation method finds the same λ_i, γ and p to match the observed transitions under each specification. In turn with similar search parameters, the estimates for the rental rate distribution are also similar. The only difference is lower minimum, as well as average, earnings at the end of the life cycle.

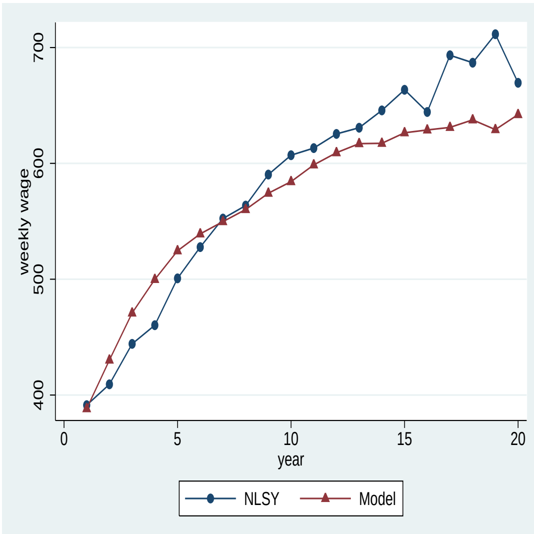
For our preferred b of 1.8, the offer rejection rate is 0 at the beginning of the life cycle but by the end it is closer to 7% as workers increase their reservation rental rate

[29]In addition to human capital accumulation, bargaining may also be an important source of within-job earnings growth (Postel-Vinay and Robin (2002) and Yamaguchi (2010)).

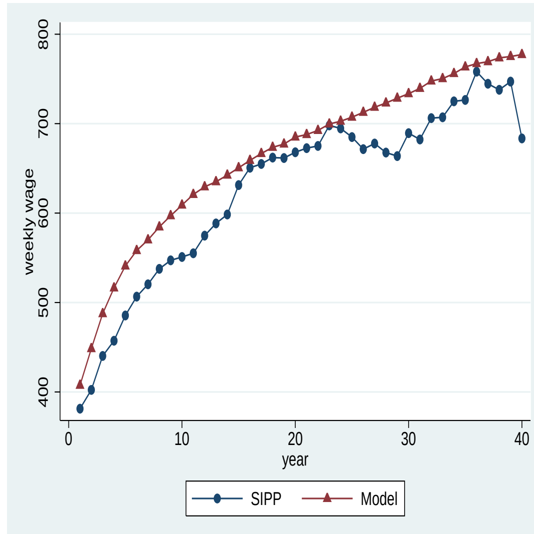
Table 3: Auxiliary Moments: Data and Model

		Moments	Data	Model
Equation	Y	X		
9	$u-j$	$cons.$	0.2642	0.1569
		x	-0.0012	0.0009
		$udur$	-0.0125	-0.0072
		$udur^2$	0.0001	0.0001
10	$j-j$	$cons.$	0.2780	0.5077
		x	0.0012	0.0027
		T	-0.0086	-0.0059
		T^2	0.0001	0.0001
		w	-0.0001	-0.0009
		w^2	0.0000	0.0000
13	initial $j-j$	$cons.$	0.1333	0.1783
		$jdur$	-0.0088	-0.0109
		$jdur^2$	0.0001	0.0001
	$j-u$	mean	0.0317	0.0301
12	lw	$cons.$	5.8391	5.8018
		x	0.0127	0.0051
		x^2	-0.0001	0.0000
		T	0.0089	0.0137
		T^2	-0.0001	-0.0001
		djj	0.1091	0.3463
	initial w	$mean(lw)$	5.8677	5.8562
		$s.d.(lw)$	0.3960	0.4642
11	Δlw	$cons.$	0.0240	0.0024
		x	-0.0004	0.0000
		x^2	0.0000	0.0000
		T	-0.0007	0.0000
		T^2	0.0000	0.0000
14	$j-j$	ex	-0.0011	-0.0006
		ex^2	0.0000	0.0000
15	lw	ex	0.0092	0.0064
		ex^2	0.0000	0.0000

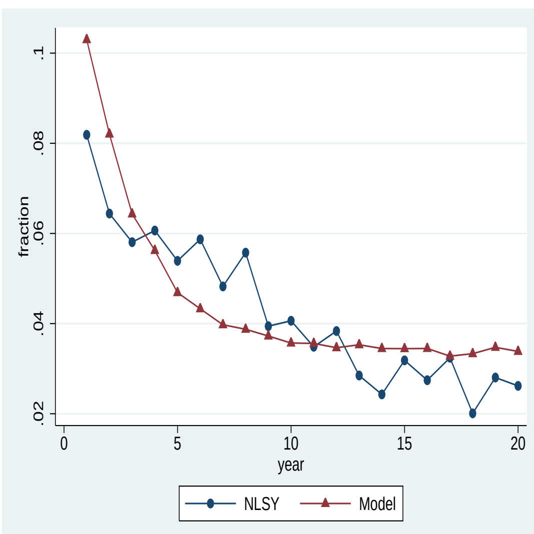
Figure 1: Model Fit



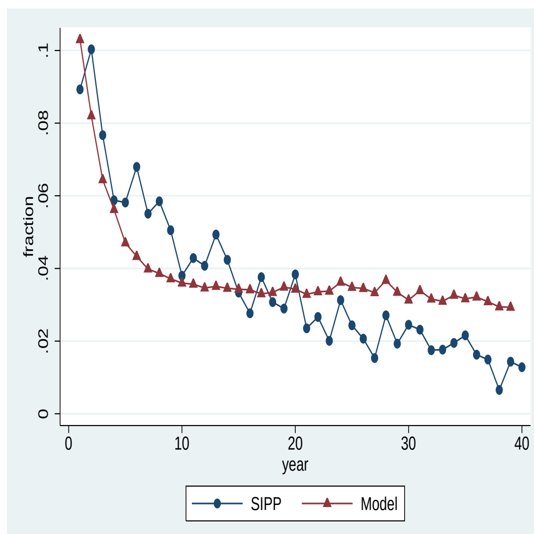
(a) Weekly Earnings (1)



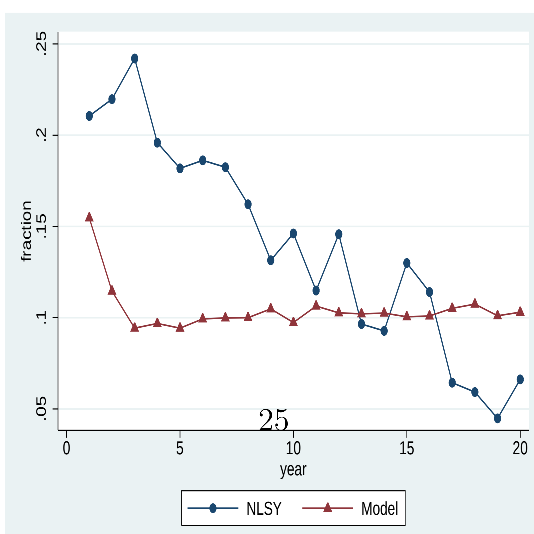
(b) Weekly Earnings (2)



(c) Job-to-Job Transitions (1)



(d) Job-to-Job Transitions (2)



(e) Unemployment-to-Job Transitions

to the value of b. While it is a common feature of equilibrium search models to have a rejection rate of 0, evidence from the literature suggests that a significant fraction of offers are rejected. For example, Blau and Robins (1990)'s finding that rejection rates were as high as 30% in 1980 has recently been echoed by Krueger and Mueller (2011) who find rejection rates in that range for 2009-2010.[30] In order to generate a higher offer rejection rate in our model one needs to increase b. Increasing b above 1.8 to 1.9 increases the offer rejection rate to 24% (32%) at the beginning (end) of the life cycle. However, this increase also substantially changes the parameter estimates as can be seen in column 3 of Table 2. Importantly λ_1 and λ_2 increase and γ decreases making search effort more efficient and less costly for both groups in order to match the transition data. In addition, with a higher offer rejection rate the mean of the rental rate distribution falls while the variance increases in order to match the earnings distribution. The largest effect though is on the human capital production function parameters. The increased search efficiency results in very high job-to-job transition rates and more earnings growth over the life cycle through search. This substantially lowers the need for human capital with a subsequent large drop in the estimate of a. In fact simulations of this model yield very little human capital investment over the life cycle and no on-the-job earnings growth causing a further misfit of that auxiliary component. The result is that there is almost no role for human capital in earnings growth over the life cycle. While we find this feature of the model interesting, we also find these results to be extreme and therefore choose b=1.8 as our preferred specification.

6 Model Simulation

To examine how individual decisions change over time Figure 2 plots human capital investment and search intensities over the life cycle for the two types of workers. Type 2 workers, the more efficient group, search more intensively on average throughout the life cycle than type 1 workers. This results in higher job offer arrival rates as shown in parts (c) and (d) of Figure 2, because the marginal returns to search are higher for type 2 workers while the search costs are the same for the two types of workers. Type 2 workers also accumulate more human capital over the life cycle than type 1 workers as shown in part (b) of Figure 2. There are two reasons for this. First, type 2 workers are searching more intensively and thus spending less time in unemployment. Second, type 2 workers also invest more in human capital, as shown in part (a), because they expect to switch jobs more often resulting in rental rates that increase more quickly.

[30] Only 60% of all offers are accepted in Krueger and Mueller (2011). However, their measure of the reservation wage is not as stark as in our model, since a significant fraction of workers reject offers higher than their stated reservation wage and an even greater fraction accept wages that are below their stated reservation wage. In addition, workers may have received more than one offer over the survey period; something that is ruled out in our model.

This is an example of the interactions that are present when both human capital and search are endogenous. In addition, type 2 workers set their reservation rates, on average, much lower than type 1 workers, as shown in part (e) of Figure 2, because employment is more valuable due to both a higher job offer arrival rate and more human capital investment on the job. Overall, a higher earnings profile and higher earnings growth over the life cycle occur for type 2 workers, as shown in part (c) of Figure 3. Finally, parts (a) and (b) of Figure 3 show how the inclusion of search heterogeneity improves the overall fit of the model. As we can see from part (a), much of the decline in the job-to-job transition rate comes from the more efficient type 2 workers. Once they move up the rental rate distribution, the likelihood of making a job-to-job transition falls. As for the unemployment-to-job transitions, part (b), the profiles are essentially flat at the individual level due to very little variation in search intensity (part (d) of Figure 2) or in reservation rental rates at a level that binds given the rental rate distribution (part (e)). However, the presence of heterogeneity does generate an initial decline overall.

To examine the interactions between human capital accumulation and job search, we conduct two counterfactual experiments. In the first experiment, we turn off on-the-job search while keeping human capital accumulation. Workers start off with the mean rental rate of human capital and keep the rental rate until the end. While there is no on-the-job search, we do include job destruction and periods of unemployment with a fixed exit rate in order to keep the total time in employment similar across the different experiments. Specifically, type 1 workers start with a mean rental rate of 4.08 and a fixed unemployment exit rate of 0.05 per quarter and type 2 with 4..15 and 0.25, respectively.[31]

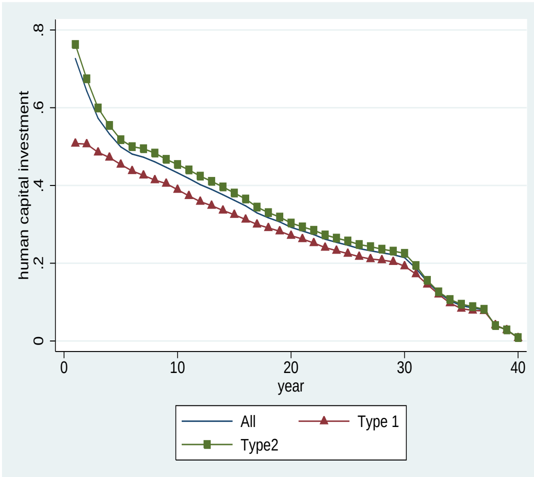
Compared to the model that has both human capital accumulation and job search, this experiment yields a lower average investment in human capital throughout almost the full life cycle, as shown in part (a) of Figure 4.[32] The human capital investment at the beginning of the life cycle is 56% more in the model with job search than the model with only human capital accumulation. Only at the end of the life cycle is human capital investment smaller in the case with both human capital and search than with only human capital accumulation. This is because, with both human capital and job search at the end of the life cycle, workers are less likely move up the job ladder yet still face job destruction, similar to the scenario with human capital only. However, the mean rental rate is much higher in the scenario with both human capital and search than that with human capital only. Hence it is more risky to invest in human capital in the former case given the possibility of ending up in unemployment in the next period (a smaller b/R ratio), than the latter case.

In the second counterfactual experiment, we turn off human capital accumulation and only allow for job search where workers start with the initial human capital but

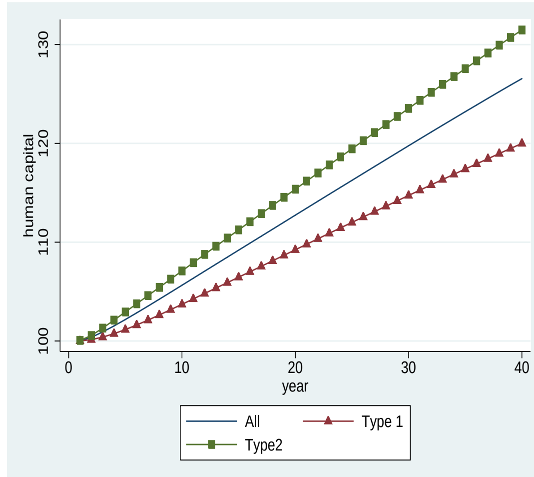
[31]These numbers are from type-specific averages in the search-only scenario.

[32]Here we compare the total investment in human capital, i.e. $h \times i$.

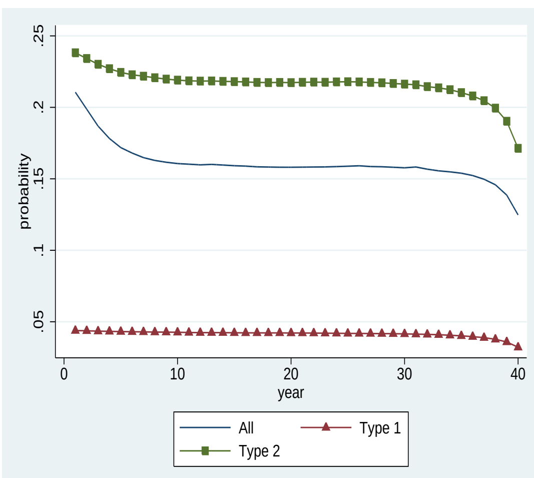
Figure 2: Model Simulation (1)



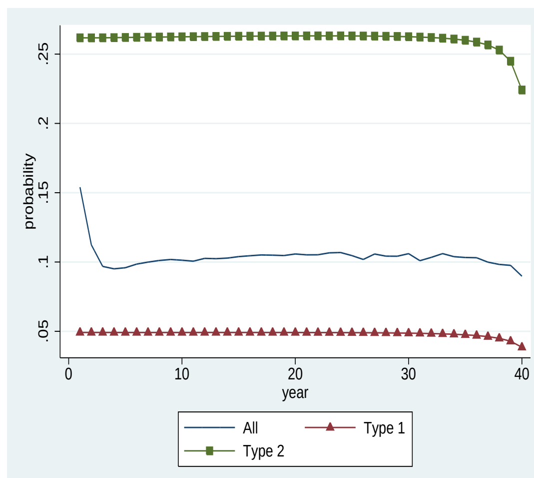
(a) Human Capital Investment



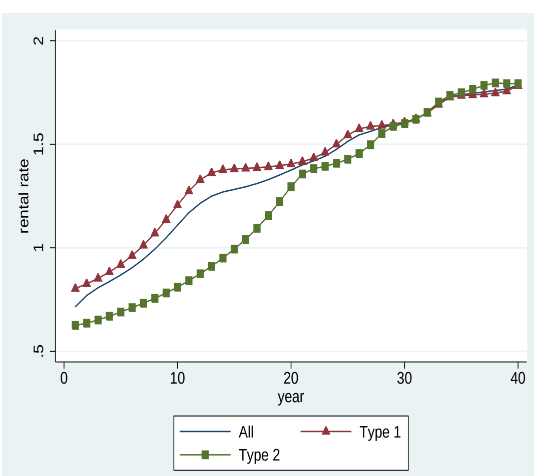
(b) Human Capital Accumulation



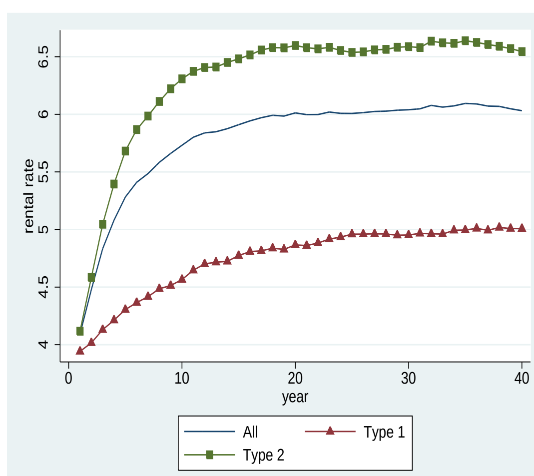
(c) On-the-Job Offer Arrival Rate



(d) Offer Arrival Rate in Unemployment

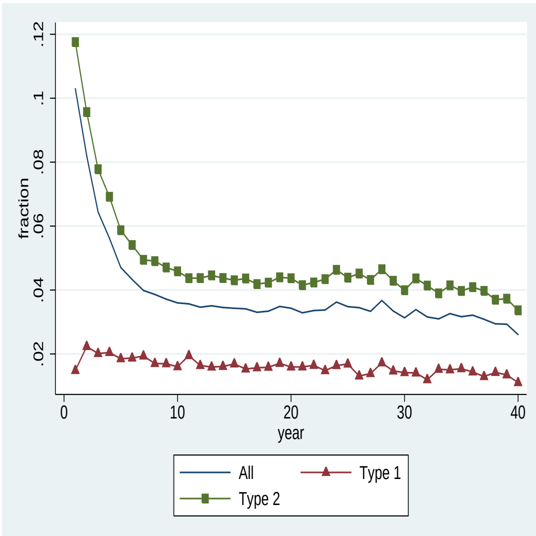


(e) Reservation Rates

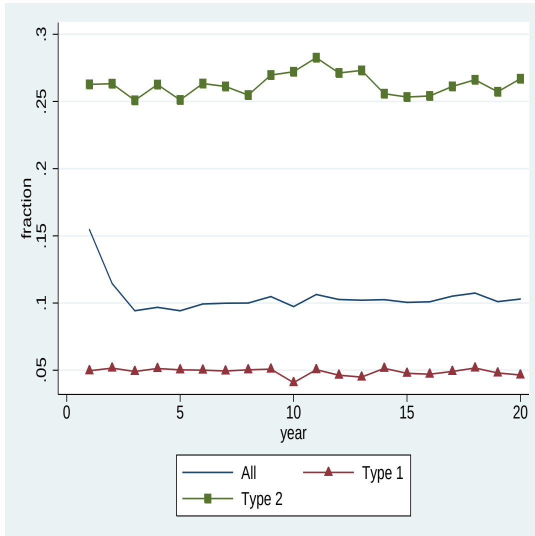


(f) Rental Rates

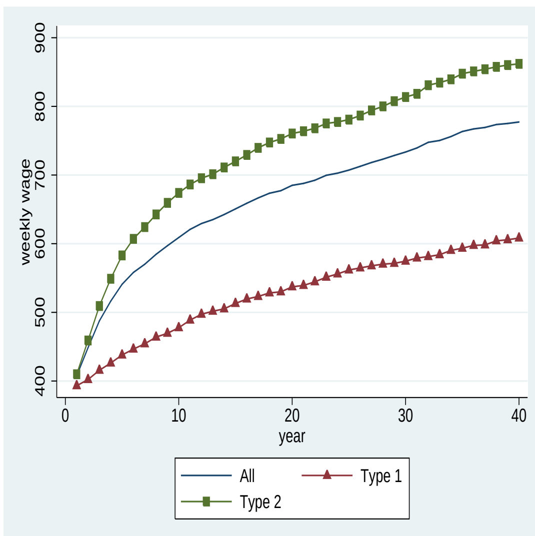
Figure 3: Model Simulation (2)



(a) Job-to-Job Transitions

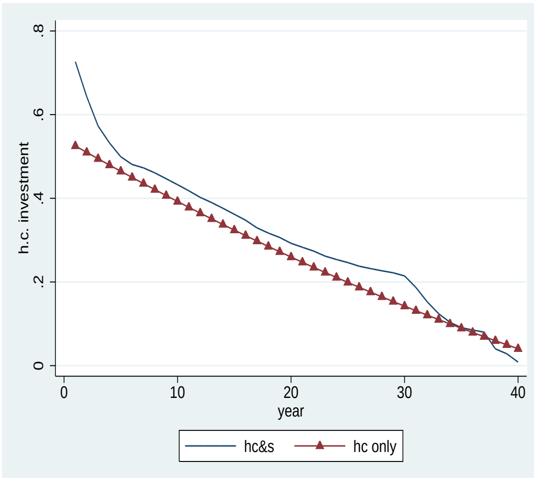


(b) Unemployment-to-Job Transitions

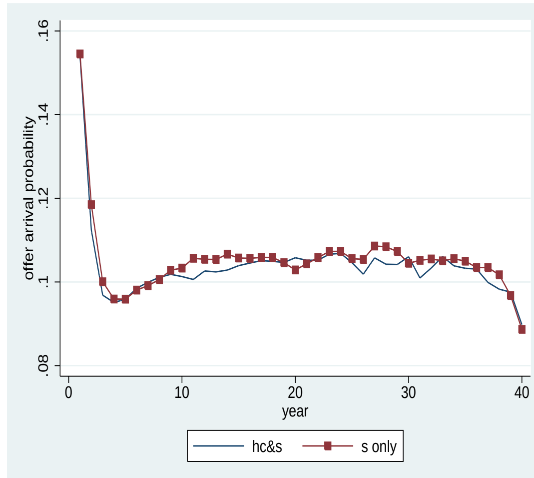


(c) Weekly Earnings

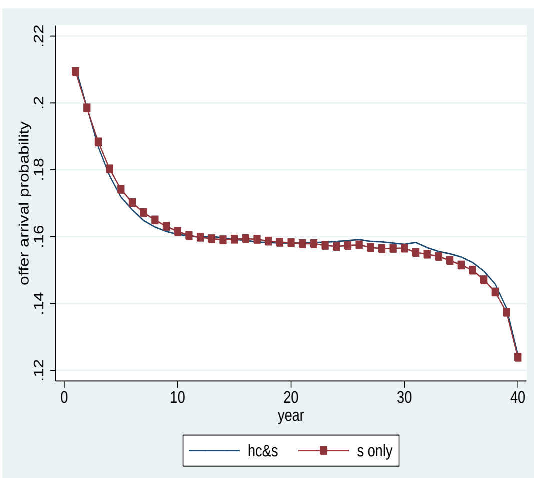
Figure 4: Counterfactual Experiments



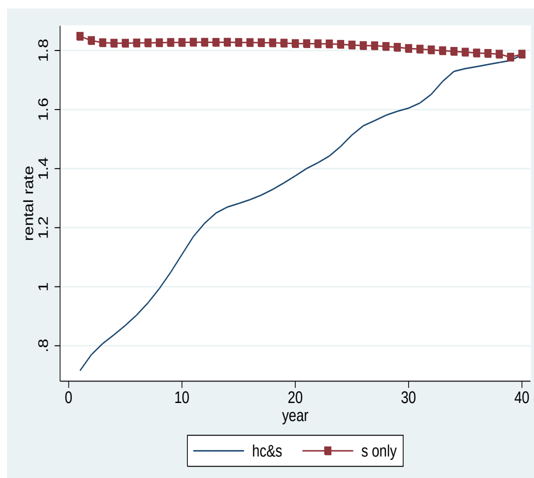
(a) Human Capital Investment



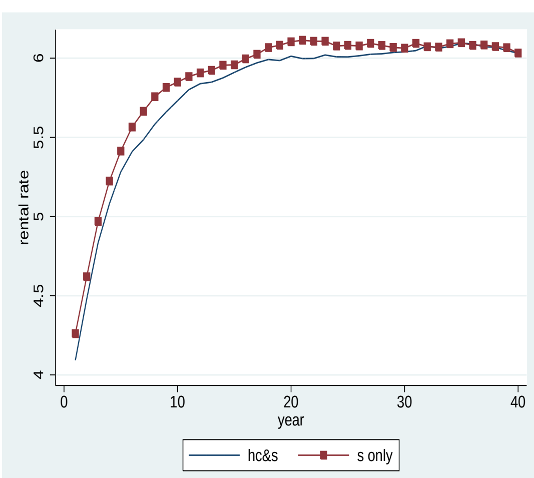
(b) Offer Arrival Rate in Unemployment



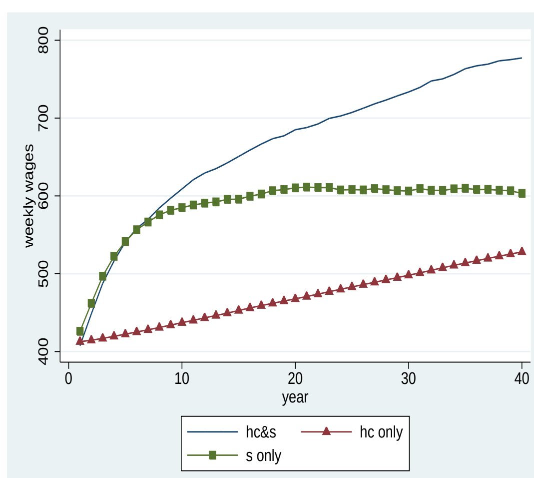
(c) On-the-Job Offer Arrival Rate



(d) Reservation Rates



(e) Rental Rates



(f) Weekly Earnings

cannot invest and accumulate more. In this case, the more significant interaction between human capital accumulation and job search is that unemployed workers reduce their reservation rates to take advantage of human capital accumulation on the job (part (d) in Figure 4). At the beginning of the life cycle, the reservation rate is more than 2 times larger in the search-only case than the case with both human capital and search. However, the search intensity under the two cases, both on the job and when unemployed, are not very different, as shown in parts (b) and (c) of Figure 4. As a result, on average the rental rate in the case with both human capital accumulation and search is lower than its counterpart in search-only case (part (e) in Figure 4).

The life cycle earnings profiles for the 3 scenarios are shown in part (f) of Figure 4: the model with both human capital accumulation and job search, the model with human capital accumulation only, and the model with search only. As we can see, the search-only model generates more earnings growth than the model with only human capital accumulation. Quantitatively, the search-only model can explain about 46% of the total earnings growth, while the model with human capital only can explain around 31% of the total earnings growth. The remaining 23% goes to the interactions between human capital accumulation and job search.

Interestingly, the decomposition of earnings growth between job search and human capital varies substantially over the life cycle, as is evident from part (f) of Figure 4. Job search accounts for 75% of the earnings growth over the first 10 years of the life cycle. Over the next 10 years, it only explains around 35%. After 20 years in the labor market, job search generates almost none of the earnings growth. In contrast, the role of human capital becomes larger and larger over the life cycle. Human capital accounts for 12% of the earnings growth for the first 10 years. The share of earnings growth due to human capital then increases to around 56% for the next 10 years. Over the last 20 years of the life cycle, human capital explains almost all of the growth in earnings. These patterns come out of the model because workers shop for jobs and try to find the best matches early in the life cycle. As workers move up the job ladder, on-the-job search becomes less valuable and search effort declines. Human capital investment also falls as workers age, but the results show that enough human capital investment is maintained such that human capital accumulation dominates earnings growth later in the life cycle. These results are consistent with Yamaguchi (2010) who finds search is more important than human capital over the first 5 years only to be overtaken by human capital later in the life cycle, but are counter to Bagger et al. (2011) who find human capital is initially more important only to be overtaken by search.

Our finding that job search is relatively more important than human capital accumulation in accounting for life cycle earnings growth seemingly diverges from the majority of the existing literature that finds the exact opposite. This discrepancy can be attributed to two reasons. First, the implications for earnings growth are sensitive to model specification. The majority of studies in the existing literature, which find that human capital accumulation is a more important source of earnings growth, assumes an exogenous search technology with no heterogeneity resulting in constant job offer arrival rates, reservation wages, and job destruction rates. Importantly it is the heterogeneity that matters. In our model without search heterogeneity human capital accumulation is predicted to be more important than job search in accounting for life cycle earnings growth, accounting for 70% or so. This is consistent with Pavan (2008) who finds that a more flexible search model with heterogeneity and varying job offer arrival rates and reservation wages fits the data better than a search model with less flexibility in search technology and hence yields different implications of interest. Second, the majority of the existing literature does not consider the interactions between human capital accumulation and job search. As a result, the reported contributions of human capital accumulation are likely contaminated because some of the human capital accumulated over the life cycle results from the interactions between job search and human capital accumulation. Our finding that more than twenty percent of the earnings growth over the life cycle stems from this interaction indicates that this interaction is an important component.

7 Conclusions

This paper presents and estimates a life cycle model that endogenizes both human capital investment and search intensity to examine the interactions between them and quantify the relative contribution of each mechanism to earnings growth over the life cycle. Two notable interactions are (1) the expectation of rising rental rates due to job search over the life cycle induces more investment in human capital almost throughout the entire life cycle, and (2) because of human capital accumulation, workers reduce their reservation rates and increase their search intensity to take advantage of human capital accumulation on the job.

Importantly we estimate a model with unobserved search heterogeneity, because it fits the data much better than a model without unobserved search heterogeneity. Workers with high search efficiency tend to invest more in human capital and search more intensively and thus have a higher earnings profile over the life cycle. Interestingly, the point estimate of the curvature parameter for the human capital production function from the model with search heterogeneity is much smaller compared to those found in the human capital literature. This is because job search generates much of the needed curvature to match the life cycle earnings profile. Based on the counterfactual experiments, a heterogeneous search model without human capital accumulation can generate around 46% of the total earnings growth while a model with only human capital can generate 31% of the total earnings growth. The remaining 23% indicates that the interaction component is substantial.

This paper adds to the existing literature on the decomposition of earnings growth between job search and human capital in two respects. First, unlike most of the existing literature, the model with search heterogeneity predicts a relatively larger role for job search than human capital. The existing studies only allow for heterogeneity in human capital but not in search and hence tend to overestimate the contribution of human capital accumulation. This may be because workers who are capable of learning are also more efficient in searching. Hence, the presumable higher earnings growth for workers with high learning ability comes not only from more investment in human capital but also from more job-to-job transitions. Therefore, in frameworks where there is only heterogeneity in human capital but not in search, human capital accumulation plays a larger role than it would otherwise. Second, the interactions or the spill-over effects between human capital accumulation and job search should be considered when decomposing earnings growth or disentangling one from the other. For example, with the interactions, the role played by job search consists of not only the conventional earnings gains through job switching, but also a "value-added" one, that is, a spill-over effect on human capital investment.

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A Monte Carlo Exercise

For the Monte Carlo exercise we use the model without unobserved heterogeneity, we suppress endogenous quits to unemployment, and we set δ equal to the true value. This eases the computational burden while still giving informative results. The true model is specified in the second column of Table 4. We simulate 40 random samples of size 500 based on the true model, assuming a 40-year life cycle. For each random sample, the moments or the coefficients from the auxiliary regressions and weighting matrix are estimated. Indirect inference is then applied to each random sample to estimate the model parameters. The means and standard deviations of the parameter estimates are presented in the third to fifth column of Table 4.

The first exercise assumes that all the information used to calculate the moments is available over the full life cycle. The estimates, as shown in column 3, are very close to the true values indicating that the proposed auxiliary model can recover the true parameters.

The second exercise assumes the information is only available for the first half of the life cycle. This is motivated by the nature of NLSY, since it does not cover the full working life of the sample participants. The majority of individuals in our final sample only have 20 years of labor market history. Theoretically, the parameter estimates should still converge to the true values with only the partial histories, since all of the structural parameters are constant over time and age. However, the estimates from partial histories may be less precise, because the auxiliary models from the first 20 years may contain only weak identification information. In particular, this may result from the loss of information on post-displacement earnings and unemployment-to-job transitions for older workers, which are helpful for identifying the search parameters and b, because investment in human capital becomes less and less valuable as workers age. The results are shown in column 4 of Table 4. The estimates are substantially nosier than those using full histories, but the true values are contained within standard confidence intervals around the estimates.

The third exercise is to test if the estimates can be improved if additional information over the full life cycle is used to augment the first half of the life cycle. In particular, we augment the moments used in the second exercise with information on job-to-job transitions and the earnings profile over the full life cycle (see equations (14) and (15)). The resulting estimates, presented in the last column of Table 4, are much improved as compared to those in the second exercise with smaller standard deviations.

Table 4: Monte Carlo Results

	True values	40 Years	20 Years	20+40
λ	0.57	0.592	0.594	0.601
		(0.055)	(0.057)	(0.062)
b	1.50	1.502	1.415	1.463
		(0.025)	(0.073)	(0.071)
γ	4.00	4.179	4.567	4.368
		(0.505)	(1.159)	(0.791)
a	0.08	0.080	0.092	0.085
		(0.001)	(0.009)	(0.006)
α	0.60	0.596	0.471	0.539
		(0.012)	(0.093)	(0.067)
h_0	6.00	fixed	fixed	fixed
μ	0.70	0.684	0.628	0.651
		(0.034)	(0.049)	(0.049)
σ	0.30	0.309	0.351	0.331
		(0.018)	(0.034)	(0.032)

B Data Issues

One key issue when implementing indirect inference is sampling from the model-simulated data in exactly the same way as the actual data are sampled. Due to the nature of the NLSY data, there are two several problems that deserve special attention.

The first is an initial condition problem. In the NLSY sample, around 33% of white male high school graduates start full-time jobs immediately after high school graduation. Recall that we set the calendar quarter that contains the high school graduation date as the first quarter in the labor market. By doing so, we produce the appearance of duration dependence in the unemployment-to-job transition even when none is present. This generates a spike in the unemployment-to-job transition rate at the first quarter, of 56%, which then drops to 21% in the following quarter. To address this, those jobs that start immediately after high school graduation are left-censored and the information on unemployment-to-job transitions at the first quarter is not used in the auxiliary regressions for both the real data and the simulated data from the model.

Second, in the NLSY during each interview respondents are asked a wage for each job held since the last interview. If a job is ongoing at the interview week, the reported wage is treated as the wage as of the interview week for that job. If a job ends before the interview week, the reported wage is treated as the wage of the last week and, hence, the last quarter for that job. Meanwhile, respondents are interviewed once a year before 1994 and once every two years after 1994. Hence wages are not available for every quarter, only for those quarters that contain the interview weeks and the last weeks of jobs. To address this sampling issue, we estimate a transition matrix of interview quarters in the NLSY sample and apply it to the model-simulated data so that we can generate an identical interview sampling scheme in the model as in the NLSY and ensure a similar selection of observations for both the model and data.